

# The Effect of Patent Protection on Inventor Mobility

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## Abstract

This paper investigates the effect of obtaining a patent on the mobility of early employee inventors. If patents serve as signals of inventor ability, they should increase the mobility of their authors. In contrast, if patents make their author's human capital more firm-specific for appropriability reasons, they should have a detrimental effect on mobility. We draw on US patent application data for the period 2001-2012 to investigate this question. Using average examiner leniency as an instrumental variable for granted patents, we find that having one additional patent granted decreases inventor mobility by about 25 percent. The estimated effect is nearly twice as big for the case of discrete technologies (chemicals and pharmaceuticals), where the appropriation effect of patents is stronger. The effect is also stronger in cases where the inventor's knowledge can be independently transferred (e.g., inventors with few co-authors). Overall, we interpret our evidence as supportive of the appropriability hypothesis.

**KEYWORDS:** inventors, mobility, patents, appropriability

**JEL Classification:** J62, O32, O34

# 1 Introduction

Since [Arrow's \(1962\)](#) observation that “*mobility of personnel among firms provides a way of spreading information*”, economists have identified labor mobility as one of the key conduits through which knowledge spillovers occur. In this respect, the mobility of high-skilled personnel responsible for technological advances is particularly relevant. Existing research has documented inter-firm transfer of technical knowledge following the move of inventors responsible for patented innovations ([Almeida and Kogut, 1999](#); [Singh and Agrawal, 2011](#)). Accordingly, scholars have also examined how mobility is shaped by factors affecting the effectiveness of knowledge transfer, including the features of the recipient firm ([Rosenkopf and Almeida, 2003](#)), the characteristics of inventors' knowledge ([Palomeras and Melero, 2010](#); [Ganco et al., 2015](#)), the match between the new employer and the inventor ([Nakajima et al., 2010](#)), and institutional factors such as covenants not to compete ([Fallick et al., 2006](#); [Marx et al., 2009](#)).

Most of the above-mentioned papers rely on patent data to identify inter-firm mobility of inventors. Even though we know that patents capture only a fraction of technological innovations and a very particular type of highly skilled workers, they are extremely useful to identify the characteristics of such innovations, the inventors who embody them, their moves across firms and the potential subsequent knowledge flows (for a recent critical assessment, see [Ge et al., 2016](#)). Nevertheless, patents do not have a neutral effect on the innovations they protect. Since they are tangible intellectual property rights that (i) publicly describe the innovation and (ii) exclude others from bringing that innovation to the marketplace for a certain time period, they may modify the behavior of the actors involved the development and implementation of the innovation. Previous research has noted that patents make it easier to trade the underlying innovations in markets for technology by making tangible the object of the transaction, especially in licensing deals ([Arora et al., 2004](#)). Furthermore, entrepreneurs who have their innovations patent-protected are better able to finance their ventures, since patents mitigate information asymmetries between innovators and investors ([Conti et al., 2013](#); [Gaulé, 2015](#); [Farre-Mensa et al., 2016](#)). In the market for inventors, patents help employers to alleviate the consequences

of their inventors' departures to competitors, by reducing the knowledge they can effectively use in their new companies (Kim and Marschke, 2005; Agarwal et al., 2009). This last set of findings suggests that patents may directly affect the relative expected value that the inventor of the underlying innovation has in the labor market and, consequently, her mobility.

In this study, we explicitly explore the effect that patenting has on the career moves of the inventors responsible for the underlying innovations. Following the existing literature on labor economics and intellectual property rights, we identify two opposite hypotheses regarding the effect of patents on inventor mobility: a *signaling hypothesis* and an *appropriability hypothesis*. According to the signaling hypothesis, patent grants would send out a publicly observable signal on the ability of the inventor. If, as suggested by Hoisl (2007), patent documents provide valuable information to identify high-performing inventors and the inventor labor market is a context affected by asymmetric information (Greenwald, 1986), then patents will send a signal to the external labor market. This signal, by reducing the amount of private information in the hands of the current employer, should increase inter-firm mobility. The appropriability hypothesis makes the opposite prediction. Since patents confer monopoly power over a given technology to their owners (usually, the employers of the inventor), they limit the amount of knowledge that a moving inventor can effectively use with her new employer (Kim and Marschke, 2005; Agarwal et al., 2009). This makes the human capital of these inventors more specific to their current employers, turning them less likely movers.

Testing the aforementioned hypotheses poses an important methodological challenge. Since patented innovations are inherently different from non-patented ones (and so are likely to be their inventors), a simple comparison of the inventors who patent with those who do not might lead to conclusions that would only mirror the underlying dissimilarities. First, firms' decisions to apply for patent protection depends on the characteristics of the given innovation (see Criscuolo et al., 2015), which may reflect the human capital of its inventor. Second, the decision to apply for a patent is likely to be affected by the dynamism of the inventor labor market, as suggested by Kim and Marschke (2005). Moreover, the set of applications that are finally granted are a selected group of innovations as well, namely those that

imply a sufficient advancement in the state of the art according to the patent office requirements (i.e., novelty and non-obviousness of the inventive step). These requirements are arguably more likely to be achieved by talented inventors. Hence, a straightforward comparison between patented and non-patented innovations is not appropriate.

We investigate the effect of patenting on inventor mobility by comparing the trajectories of inventors with different numbers of applications granted. In order to be able to estimate the causal relationship, we use variations in leniency across patent examiners as an exogenous source of variation in the granting of patents. Patent examiner leniency has been recently used as an instrumental variable to estimate the effect of patents on subsequent cumulative innovation (Sampat and Williams, 2015) and on venture capital-backed startup success (Gaulé, 2015; Farre-Mensa et al., 2016). The validity of the instrument is supported by interviews to employees of the United States Patents and Trademarks Office (USPTO) regarding the allocation of patent applications to examiners (Cockburn et al., 2003; Lemley and Sampat, 2012), as well as by our own exogeneity tests.

Our empirical analysis is based on the career trajectories of 69,136 inventors who filed their first patent application between 2001 and 2012 in the USPTO. This sample represents a selection of inventors who are in their early careers, that is, in their ten first years (at most) of inventive activity. We select these inventors for two main reasons. First, the initial steps in an inventor’s career are more likely to be affected by the outcome of one or a few patent applications. Thus, if an effect of patent grants on mobility exists, it will be more clearly detected for inventors at the beginning of their career. Moreover, regression to the mean in random processes eliminates variations in average patent examiner leniency among inventors with a large number of applications.

By identifying individual inventors’ careers from patent application data, our results point out to a negative effect of patenting on mobility. In particular, one additional patent application granted (due to a “lucky” examiner assignment) decreases an inventor’s probability of changing employers by 25 percent. This negative effect increases to 44 percent in “discrete” technologies such as pharmaceutical and chemicals, where individual inventions are more clearly linked to marketable prod-

ucts and patent rights protect them more effectively (Cohen et al., 2000). On the other hand, the estimated effect is much weaker in “complex” technologies (such as electronics) where a given product is typically associated with many potentially patentable elements, meaning that an individual patent confers much less protection to the final product. Overall, these results suggest that, by providing firms with monopoly rights over a given technology, patents make the human capital of the creators of the underlying innovation more specific to their current employers. This appropriation effect of patent grants dominates any signaling effect that may exist and substantially reduces the mobility of patenting inventors in our sample. Additional tests show that the negative effect of patenting on mobility is stronger for inventors with fewer co-authors and for inventors working outside the technological core of their firm, suggesting that the appropriation effect that patents confer is stronger in the absence of other sources of firm-specific human capital. Finally, and also consistent with the appropriability hypothesis, we document that patents most strongly decrease the mobility of inventors towards firms that work in the same technological core areas of their current employers.

The results of our study add new insights in several domains. First of all, we contribute to research on knowledge transfer and inventor mobility by showing that the institutional role of patent offices is not neutral to mobility. While scholars have examined a series of institutional factors (Fallick et al., 2006; Marx et al., 2009; Marx, 2011; Png and Samila, 2015) and inventors characteristics (Hoisl, 2006; Palomeras and Melero, 2010) as antecedents of knowledge workers’ mobility by using patent data, little is known about whether and how the mobility of those employees is itself affected by patents. Our study aligns with previous work by Kim and Marschke (2005), Agarwal et al. (2009) and Ganco et al. (2015), which suggest that patents and patent enforcement by firms limit the amount of knowledge that moving inventors can effectively transfer to their new employers. Second, our paper adds an additional dimension to the ongoing debate on the role of the patent system. Beyond other important issues, such as whether patents provide optimal incentives to invest in R&D (Boldrin and Levine, 2013) or whether they block follow-on innovation (Sampat and Williams, 2015), our findings indicate that patents increase the firm-specificity of the human capital of their inventors. This suggests, for example,

that patents shift incentives to invest in inventive skills from employee-inventors to patent-holding employers. Finally, our results have an important methodological implication. Many research questions in the area of innovation have traditionally been addressed with data on granted patents, from mobility studies to knowledge spillovers estimations to co-inventor network analyses. Our evidence indicates that future research should take into account the effect of patent grants on the behavior of inventors and subsequent knowledge flows in order to avoid potentially biased results.

## 2 Background

Based on two different streams of literature, two opposite hypotheses arise concerning the potential effects that obtaining a patent may have on the career prospects of the inventor responsible for the underlying innovation: a *signaling hypothesis* and an *appropriability hypothesis*.

The signaling hypothesis stems from the observation that, in general, when current employers are better informed than alternative employers in the labor market about the quality of their individual employees, worker mobility is inefficiently low (Greenwald, 1986). Therefore, signals that reduce information asymmetries between current and alternative employers will be associated with increases in mobility. Patents have been argued to work as signals of firm quality in situations of asymmetric information, such as the entrepreneurial finance market (Long, 2002; Hsu and Ziedonis, 2013; Conti et al., 2013). On the one hand, patents are costly to obtain by firms, as they come as the result of a sorting process by the patent office. Therefore, they may act as credible signals of the potential value of the underlying project. On the other hand, they contain readily codified technical information about the innovation that is easily accessible by observers and may be costly to retrieve otherwise. This information may be valuable to infer unobservable firm characteristics to which patents are associated (Long, 2002). Empirical evidence indicates that venture-capitalists increase their valuation of start-ups that receive patent grants, especially in the more uncertain early financing rounds (Hsu and Ziedonis, 2013). Moreover, Farre-Mensa et al. (2016) provide causal evidence on the effect of patent

grants on the probability of raising new venture-capital funding, particularly in contexts of highly asymmetric information. This suggests that patents act as de facto information mechanisms in the entrepreneurial capital market.

Analogously, we can expect patents to work as signals in the labor market for inventors. Apart from providing the technical details of the innovation, patents also provide a list of the corresponding inventors. Since the features of the patented innovation are expected to be closely related to the characteristic of its authors, patents may reveal information on inventor quality to the labor market. In particular, the granting decision by the patent office provides information on a dimension of inventor quality that is otherwise very costly to observe: her ability to innovate. As [Schönberg \(2007\)](#) documents, employers are particularly likely to enjoy private information about the ability of highly educated employees. Patent grants, therefore, would reduce the amount of private information in the hands of the inventors' current employer, reducing in turn his ability to retain them at relatively low wages ([Waldman, 1984](#); [Greenwald, 1986](#)). Consequently, by providing a signal to the labor market on the quality of the inventors responsible for the innovation, patent grants may increase inventor mobility<sup>1</sup>. [Toivanen and Väänänen \(2012\)](#) find results that are consistent with a signaling role of patents in their analysis of the wage effect of patenting for the population of Finnish inventors. They report returns to inventorship that depend significantly on observable indicators of the quality of their patents (i.e., patent citations). Therefore, we expect that under the signaling hypothesis patent grants will increase inter-firm inventor mobility.<sup>2</sup>

Alternatively, the appropriability hypothesis builds upon the idea that a patent provides its holder with monopoly rights to exploit the underlying piece of technology. Labor contracts of R&D workers typically include provisions by which employers retain property rights over their employees' inventions. This implies that patents

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<sup>1</sup>Note that if patents work as signals of inventor ability and employers have alternative means to protect their intellectual property, they may incorporate this ability-disclosure cost in their patent-filing decisions, with the result of a lower propensity to file. In empirical terms, however, inventor ability signaling does not seem to be a relevant element in firms' patenting decisions (see [Hall et al., 2014](#))

<sup>2</sup>Note that we discuss here the signaling effects of patent grants. We have to take into account, however, that: (i) the patent application contains information about the innovation and (ii) the application is usually made public before the grant -this occurs at the 18th month after application, except in the rare events that either the patent is granted before that date or the firm decides to opt out from publication and give up international protection. Therefore, we are in fact examining the certification signal provided by the patent grant in excess of the technologically-oriented signal provided by the patent application. See a more detailed discussion on the Conclusion section of the paper.

effectively constrain the inventor from freely using the protected knowledge. In that case, patent rights may be interpreted as causing the inventor's human capital to become specific to the patent-holder (i.e., the inventor's human capital becomes relatively less valuable for alternative employers).

The ability of competitors to replicate an innovation can be clearly enhanced by employing its original inventor. Patents, by preventing the unauthorized commercial exploitation of the corresponding technological replicas, may then reduce the attractiveness of the inventors in the labor market. This argument is closely related to the observation by [Kim and Marschke \(2005\)](#) that, in the absence of patent protection, inventors can easily take ideas and projects with them when they switch employers. Such transfer of knowledge is substantially restricted if the incumbent employers hold corresponding patents. Accordingly, the mentioned authors show evidence that innovative firms tend to file for patent protection more in contexts of highly dynamic R&D labor markets. Recent research on the association between employers' reputation for litigiousness (in terms of patent enforcement) and the mobility of their inventors also provides evidence in this direction. [Agarwal et al. \(2009\)](#) report that mobile inventors who authored patents with a former employer are less likely to use the knowledge related to those patents in their new employment if their former employer has a reputation for being a tough enforcer of property rights. In the same line, [Ganco et al. \(2015\)](#) provide evidence that the outbound mobility of authors of patented innovations is significantly lower in innovative firms with a strong reputation for patent litigation.<sup>3</sup> Therefore, if patents make the knowledge of the inventor unusable outside the current firm for replication purposes, competitors will be less interested in poaching the inventor.

Inventors' knowledge may also be a helpful resource for the successful implementation of the innovation by the patentholder. By legally excluding competitors, patents may allow their patent holders to obtain monopoly profits when bringing the innovation to the market. The involvement of the inventor in implementation activities can be expected to enhance the maximization of such profits. The development of the innovation into an actual product (or process) ready to be launched

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<sup>3</sup>Outside the realm of patent enforcement, [Png and Samila \(2015\)](#) show that the mobility rates of qualified workers is lower in US states with stronger enforcement of trade-secret laws.

to the market (or internally implemented) is not a trivial task and it usually profits highly from the involvement of the creators of the innovation. In a study of licensing contracts of patented inventions in the biomedical industry, [Hegde \(2014\)](#) reports the use of clauses specifying the complementary knowledge that should be transferred to the licensee along with patents in order to successfully develop the innovation. Some of these clauses explicitly specify the requirement of personal involvement of the inventors in the process, as well as a monetary compensation for their effort. These cases illustrate the importance of non-codified knowledge for the transfer and implementation of patented technologies. [Maurseth and Svensson \(2015\)](#) provide further suggestive evidence of the importance of the inventor's tacit knowledge for the success of the innovation in the market. In their study of a sample of commercially exploited Swedish patents generated by small firms, they find that (self-reported) inventor involvement in the commercialization phase is positively related to the success of the innovation in the market.

Hence, if patents (i) prevent the inventor from outside replication and (ii) give the patent-holder monopoly power that can only be fully exploited by keeping the inventor in-house, under the appropriability hypothesis we expect that patent grants will lead to reduced inter-firm inventor mobility.

### 3 Data

Our paper combines data from several sources. Our starting point is the USPTO Patent Examination Research (PatEx) dataset, which sources its information from the Public Patent Application Information Retrieval (PAIR) database. PAIR contains detailed information on patent applications filed with the USPTO. For each application, it includes characteristics of the applications such as filing date, application type, patent class and subclass codes and current application status and also data about the examination such as the identity of the assigned examiner and the art unit to which he belongs. From this dataset, we identify every original utility patent application filed between 2001 and 2012, which consisted of 3.6 million applications. We are constrained to this time period due to data availability. The PAIR dataset contains data only on applications that have been published (i.e. open to

public scrutiny) and it was not until late 2000 when applications were made public before the patent was granted, following the implementation of the American Inventors Protection Act (AIPA). This means that, from November 2000 on, publication happens regardless of grant but, before that, only the applications that were finally issued as patents were published. As [Graham et al. \(2015\)](#) report, PAIR has a very good coverage (95%) of the regular utility filings from 2001 to 2012 (after that, truncation due to publication lag affects coverage).<sup>4</sup>

We next turn to the information available at the USPTO Patent Assignment Dataset, since the PAIR database does not identify the assignee (i.e., the firm) responsible for filing the patent. Before September 2012, the USPTO considered that the presumable owner of a patent application was the inventor. However, inventors typically have a contractual obligation to transfer their ownership to their employer. In order to do so, it was necessary to submit to the patent office a chain of title from the original owner (i.e. the inventor) to the assignee (i.e. the firm) so that the legal assignment could be fulfilled<sup>5</sup>. The dataset tags those assignments, allowing us to identify the assignee and presumable employer of an inventor. From our original set of patent applications, we identify 2.8 million applications that are assigned from inventors to their firms.

Thereafter, we use data from the PatentsView initiative ([www.patentsview.org](http://www.patentsview.org)) in order to identify the inventors listed in our sample of applications and compile their career histories. This dataset contains the results of the disambiguation algorithm specific for inventor data provided in [Li et al. \(2014\)](#) and [Balsmeier et al. \(2015\)](#), which allow a robust identification of individual inventors across patent applications (since 2001) and granted patents (since 1976).<sup>6</sup> We can identify through this data 2.1 million disambiguated individual inventors. This initial set of inventors is substantially reduced due to different restrictions we impose. First, since we are

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<sup>4</sup>The remaining uncovered applications are either those that opted out of pre-grant publication and were not issued or those that were abandoned before the 18-month publication lag ([Graham et al., 2015](#)). According to these authors, who had access to internal USPTO application records, the applications covered by PatEx are very similar to the population of USPTO applications.

<sup>5</sup>See [37 CFR 3.71 \(pre-AIA\)](#), [35 U.S.C. 261](#) and [Marco et al. \(2015\)](#) for details.

<sup>6</sup>We are grateful to the PatentsView team for sharing this data with us. PatentsView is supported by the Office of Chief Economist in the USPTO, with additional support from the U.S. Department of Agriculture (USDA). The PatentsView platform was established in 2012 and is a collaboration between USPTO, USDA, the Center for the Science of Science and Innovation Policy at the American Institutes for Research, the University of California at Berkeley, Twin Arch Technologies, and Periscope.

interested in calibrating the impact of patents on the early career of inventors, we select only those inventors with no patenting experience prior to observing them in our sample period (i.e. before 2001). Second, given our aim to detect the impact of the granting decision by the patent office, we focus on inventors who receive at least one decision on a patent application during our sample period. In particular, we require that they receive the first decision on their applications prior to 2012 in order to ensure we have at least a nine months window for observing mobility for the last cohort in the data.<sup>7 8</sup>

Given the interest of our study on employee inventors, we further restrict our sample to inventors who started their careers (as measured by their patent filings) working at a company. In order to be able to capture them, we select applications assigned to originating firms included in the Standard and Poor’s (S&P) Capital IQ database, which provides names and transactions (such as mergers and acquisitions) of the most extensive set of public and privately held U.S. firms (to the best of our knowledge). In order to match firm names from Capital IQ with assignee names, we first apply the name standardization procedure used in the NBER patent data project<sup>9</sup>. We then run the Jaro-Winkler algorithm (developed to assist in the disambiguation of names in the U.S. Census) to correct for typos and misspellings, grouping together records with an overlap of 90% or higher. Finally, we keep the final list of standardized assignee names that coincide exactly with firm names in Capital IQ.

Following previous literature, we infer inventor mobility based on the change in assignee between two consecutive applications (see, e.g., Almeida and Kogut, 1999; Trajtenberg et al., 2006; Marx et al., 2009; Singh and Agrawal, 2011; Ganco et al., 2015). This approach has a number of acknowledged limitations (Palomeras and Melero, 2010; Ge et al., 2016). First of all, identifying inventors through the names appearing in patent documents is a process subject to errors. We mitigate them by using Balsmeier et al. (2015) disambiguation algorithm. Other important

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<sup>7</sup>Note that our observation period runs effectively until September 2012, when the regime on the previously mentioned legal assignment from inventors to their firms changed.

<sup>8</sup>To deal with censoring, we construct two alternative datasets that include, for each inventor, only: (i) the first patent application filed after the first decision, or (ii) all her applications filed in a fixed 5-year window. Our empirical findings are robust when replicated with these alternative datasets.

<sup>9</sup>See <https://sites.google.com/site/patentdatapoint/Home>.

sources of misclassification errors in tracking mobility with patent data are <sup>10</sup>: the inability to detect the exact point in time when moves take place (irrelevant for our study), and the recording as moves of contract R&D, collaborations, or mergers and acquisitions. We address this last problem by imposing some restrictions in order to consider a change in assignee as an actual move: (i) we do not consider as moves changes in assignee that imply returns to an original employer in less than one year from the supposed move (as in Ge et al., 2016), under the assumption that they probably reflect contract research or collaborations; and (ii) we do not consider as moves the apparent changes in employers due to mergers and acquisitions, detected through the information provided by Capital IQ. The existence of some remaining minor misclassification errors is unavoidable due to the nature of the large-scale representative sample used in our study.

Thus, our final sample consists of inventors who started their research lives in one of our identified Capital IQ firms during the period 2001-2011 and who receive the first decision on their applications prior to 2012. We track inventors from their first application until either they move or until their last application (during the sample period) with the originating firm. It is important to underline that we can detect moves only when inventors file an application. The resulting data comprises 69,136 first-time inventors employed by 2,883 originating firms and who file 404,016 patent applications during the sample period. In total, we detect 13,984 first-employer changes for those inventors, averaging 0.20 moves per inventor.

## 4 Econometric modeling strategy

### 4.1 Baseline specification

In order to identify how the approval of an inventor’s patent application affects subsequent mobility, we estimate the likelihood that an individual changes her employer between application year  $t$  and application year  $t + 1$ , conditional on not having moved at  $t$ . We use a linear probability model to estimate the hazard that

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<sup>10</sup>These errors are highlighted in Ge et al. (2016)’s attempt to detect the misclassification problems produced by the use of patent data to track mobility. The authors compare the mobility detected with patent data with the mobility inferred from a small (and unavoidably biased) sample of LinkedIn public and self-reported profiles by patenting inventors. Because of the lack of representativity of their sample, their results must be interpreted with caution.

an inventor moves. Consider:

$$Probability_{it} (Y_{i,t+1} = 1) = \alpha + \beta Patents\ granted_{it} + \gamma Z_{it} + \delta S_i + \varepsilon_{it}, \quad (1)$$

where  $i$  indexes inventors and  $t$  indexes application year (i.e., the number of years in which the inventor has been observed filing at least one application to that point). The dependent variable,  $Y_{i,t+1}$ , is an indicator that equals one if an inventor moves between  $t$  and  $t+1$ . Note that we consolidate the information on application records to an annual basis, so that our measure of mobility records whether the inventor changed employer at least once during that observation window. Our main variable of interest,  $Patents\ granted_{it}$ , is the total number of patents issued to inventor  $i$  up to (and including) spell  $t$ . The vector  $Z_{it}$  contains a range of time-variant covariates. First and most importantly,  $Z_{it}$  contains the total number of applications filed by inventor  $i$  up to spell  $t$ . We also condition on the time elapsed since the inventor's first decision year, allowing mobility decisions to be shaped by seniority. In order to account for inter-sectorial differences in mobility rates, we include indicators for six non-exclusive NBER categories in which applications are classified. Finally,  $S_i$  represents the year in which the inventor receives her first decision by the patent office. This cohort indicator controls for the fact that inventors entering later in the panel have less time to move than those entering earlier. We cluster standard errors at the inventor level.

## 4.2 Identification

An important concern with the specification discussed above is that  $\beta$  cannot be straightforwardly estimated in a consistent way if the probability of receiving a patent on an innovation is correlated with unobservable characteristics that also affect mobility. For example, inventors of higher ability may be more likely to produce innovations that satisfy the patentability criteria and, at the same time, they are more likely to be hired away (Palomeras and Melero, 2010). Therefore, any potential effect we may detect in a direct OLS estimation of Equation (1) is not necessarily causal, but may just reflect the selection of the type of inventors whose applications are more frequently granted.

To overcome this identification challenge, we propose to use examiner leniency as an instrument for whether an inventor’s applications are approved by the patent office and estimate Equation (1) using a two-stage least squares (2SLS) approach (see [Gaulé, 2015](#); [Sampat and Williams, 2015](#); [Farre-Mensa et al., 2016](#)). This instrument was first proposed by [Sampat and Williams \(2015\)](#) based on the observations by [Lemley and Sampat \(2012\)](#) and [Cockburn et al. \(2003\)](#) on the process and outcomes of patent examination at the USPTO. We next describe this process to illustrate the rationale for the instrument.

#### 4.2.1 The rationale for the instrument: the examination process

Patent examiners sitting at the Patent Office are a key figure in the examination process of a patent application. Their decisions determine its eventual approval or rejection. Recent studies suggest that the odds of getting a patent granted depend on the characteristics of the particular examiner assigned to the application ([Lemley and Sampat, 2012](#); [Frakes and Wasserman, 2016](#)). In their sample, [Lemley and Sampat \(2012\)](#) find a 11 percentage point difference in the grant rate between the least and the most experienced examiners who check applications related to a given technology. [Frakes and Wasserman \(2016\)](#) report differences in the odds of patent approval by examiners according to their cohort (i.e., the year in which they were hired) and they attribute it to differences in the training received, which mirrored the patent office policies at that time. There is also evidence that certain characteristics of the granted patents differ by examiner<sup>11</sup>. [Cockburn et al. \(2003\)](#) and [Lichtman \(2004\)](#) acknowledge that patent examination is not a mechanical process and, therefore, examiners necessarily enjoy certain discretion in how they conduct it and on its outcome. Nevertheless, the allocation of applications to examiners at the USPTO follows certain structured steps that guarantee a virtually random assignment within a given technological area ([Cockburn et al., 2003](#); [Lemley and Sampat, 2012](#)).

At the USPTO, patent applications are received by a central office, where they

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<sup>11</sup>In a small and very selective sample (180 granted patents brought to the Court of Appeals at the end of the nineties), [Cockburn et al. \(2003\)](#) note that characteristics such as prior citations introduced by the examiner, citations they receive afterwards or the odds to be declared invalid by the courts vary with the characteristics of the examiners.

are assigned an application number, assigned patent class and subclass codes and allocated accordingly to one of the “art units” in charge of the examination process. Art units are groups of examiners that are specialized in a given set of technologies (there are more art units than patent classes, but fewer than subclasses). Once a patent is allocated to an art unit, a “supervisory patent examiner” (SPE) receives the application and assigns it to a specific examiner. Each art unit is an independent administrative division and has discretion on the way the work is organized, including how applications are allocated to examiners. Interviews with patent examiners conducted by [Lemley and Sampat \(2012\)](#) reveal that the supervisory examiners make most final decisions on assignments of applications to examiners on a quasi-random basis (e.g., according to docket management needs, or following arbitrary rules such as the last digit of the application number). There is no evidence from these interviews that SPEs do any substantive evaluation of applications in order to detect their patent-worthiness. Therefore, it is unlikely that they assign applications to certain examiners according to this characteristic. Both [Lemley and Sampat \(2012\)](#) and [Sampat and Williams \(2015\)](#) show that patent applications assigned to lenient and strict patent examiners look similar in observable characteristics at the time of application (number of pages, family size and number of claims). We replicate in our *Appendix I* this exercise for other relevant pre-determined factors such as the size of the applicant or the references to patent and non-patent literature submitted in the application. Our results do not show a significant relationship between these factors and examiner leniency either. Hence, the evidence at hand suggests that the assignment of applications to examiners can be reasonably assumed to be essentially random within a given art unit. Consequently, we follow [Sampat and Williams \(2015\)](#), [Gaulé \(2015\)](#), and [Farre-Mensa et al. \(2016\)](#) in using examiner’s leniency as an instrument for application approval.

#### **4.2.2 The instrument: Average Examiner’s Leniency**

Our objective is to obtain an instrumental variable for the number of applications granted to an inventor up to a given moment of time. We start by operationalizing examiner leniency at the application level. In the spirit of [Gaulé \(2015\)](#), we compute

a time-varying measure of leniency as follows:

$$E_{jkat} = \frac{Grants_{kat} - 1(Grant_j = 1)}{Reviews_{kat} - 1}, \quad (2)$$

and

$$U_{jat} = \frac{Grants_{at} - 1(Grant_j = 1)}{Reviews_{at} - 1} \quad (3)$$

where  $E_{jkat}$  is the approval rate of examiner  $k$  belonging to art unit  $a$  assigned to review patent application  $j$  submitted at time  $t$ .  $Reviews_{kat}$  and  $Grants_{kat}$  are the numbers of applications examiner  $k$  has reviewed and granted in art unit  $a$  that have the same application year as  $j$ .<sup>12</sup> Similarly,  $U_{jat}$  is the approval rate of art unit  $a$  and is constructed as the share of reviewed applications filed in the same year as application  $j$  that were granted by art unit  $a$ , excluding the focal patent.<sup>13</sup> The difference between  $E_{jkat}$  and  $U_{jat}$  is hence the relative leniency faced by an inventor who files patent application  $j$  in year  $t$ , assigned to examiner  $k$  within art unit  $a$ . For a single patent application, the corresponding examiner relative leniency,  $E_{jkat} - U_{jat}$ , is a suitable instrument for whether that application is granted. However, we are interested in obtaining an instrument for the inventor's total number of applications granted up to a given moment of time. We account for this by averaging  $E_{jkat} - U_{jat}$  across all patents applied for by inventor  $i$  up to year  $t$ :

$$L_{it} = \frac{1}{n_{it}} \sum_{j=1}^{n_{it}} (E_{jkat} - U_{jat}) \quad (4)$$

Thus, unlike previous literature using examiner leniency as an instrument, our study averages leniency at the inventor level. This prevents us from using within-art-unit technology fixed effects in our main specifications. In *Appendix II* we provide some evidence suggesting that this is not an important concern.

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<sup>12</sup>Given that there may be concerns of measurement error in leniency when the set of applications is small, we define some threshold values (10, 20, and 50) and experiment considering only cases with a number of reviewed applications per examiner, year and art unit that exceeds these thresholds. If anything, results are stronger with these restrictions.

<sup>13</sup>Note that our instrument differs from the one proposed by [Gaulé \(2015\)](#) in two aspects. First, while the author considers the overall approval rate of an examiner, we follow [Sampat and Williams \(2015\)](#) and [Farre-Mensa et al. \(2016\)](#) by adjusting for each art unit. Our key reason for doing so is that in our sample period, on average, 39% of examiners reviewed patent applications for multiple art units in the same year. Second, our equations also differ in the denominator since we use the number of patent applications reviewed rather than the number of applications filed. Nothing hinges on the use of the leniency measure in [Gaulé \(2015\)](#), however.

## 5 Main results

### 5.1 Patent grants and inventor mobility

Table 1 provides descriptive statistics of all variables used in this paper. The unit of observation in our analysis is the inventor-application year combination. Accordingly, the figures indicate that, on average, 11% of inventors change employers between two application years. Inventors are, on average, responsible for 2.24 granted patents. Table 2 contains the main results. In column 1 of Table 2, we begin with the OLS estimates of the baseline specification relating mobility to the number of patents granted and additional controls. We find a weak, positive and significant correlation between patent grants and mobility. This results is not causal, however. As argued above, there are reasons why we should expect unobservable factors to affect both the extent to which inventor’s patent applications are approved by the USPTO and subsequent mobility. Moving to the instrumental variable approach, column 2 presents the first stage where we regress the number of patents issued on *examiner leniency* (and all the other controls). As expected, the instrument is positive and highly significant. A one standard deviation increase in the leniency of examiners assigned to review an inventor’s patent applications is associated with a 0.041 standard deviations increase in the number of patents issued. The first-stage F-statistic of the excluded instrument is large (796) and well above the rule of thumb for weak instruments (see, e.g., [Stock and Yogo, 2005](#)), indicating that the instrument explains a substantial part of the variation in granted patents. Column 3 reports the result from the second-stage regressions estimating Eq. (1), with the main variable of interest replaced by the fitted value of *# of patents issued* from the first-stage regression. The coefficient is strongly negative and significant at the 1% level. The point estimate implies that an exogenous increase in one successful patent application reduces the probability of moving by 2.8%, which represent a 25% decrease over the conditional sample probability of 11%. This is a result of economic significance. The substantial difference between OLS and IV estimates highlights the importance of controlling for the endogeneity of patent grants, and indicates a strong positive correlation between *# of patents issued* and the disturbance in the mobility equation, inducing a large upward bias if we treat USPTO grant decisions

as exogenous.

For the ease of estimation and interpretation, we use linear probability models as our main specifications throughout the paper. In column 4 of Table 2, though, we report the results from a Probit model where we implement the instrumental variable estimator by using the control function method (see [Blundell and Powell, 2004](#)). This leads to qualitative and quantitative similar results for the coefficient on *# of patents issued*, and hence reassures that our linear 2SLS models provide reasonable approximations to average partial effects as suggested, for example, by [Wooldridge \(2014\)](#).

The instrumental variable specifications provide strong evidence that patents cause, on average, a decrease in the subsequent mobility of early-career inventors. This result seems consistent with the prediction of the appropriability hypothesis. One concern with this evidence is that the average negative effect might hide some relevant positive effects of patents associated with signaling at the earliest stages of an inventor’s career. To deal with this point, we perform two robustness checks that are presented in the last two columns of Table 2. First, it is possible that only the first patents obtained by an inventor reveal relevant information about her quality to the market, while all of them contribute to make her knowledge specific to her employer. This reasoning would imply a non-monotonic relationship between patent grants and mobility. To address this possibility, we consider including in our model the square of the instrumented term of the number of patents issued. As column 5 shows, this quadratic term is close to zero and not statistically significant, whereas the linear term remains negative and significant. Second, signaling effects are expected to show up more intensely the closer the inventor is to the beginning of her career. We evaluate this possibility empirically by including the (instrumented) interaction between *# of patents issued* and the years of experience since the first decision.<sup>14</sup> Column 6 shows that the interaction term enters positively but not significantly into the mobility specification, suggesting that the observed negative impact of patents is, if anything, stronger for less experienced inventors. None of these results is therefore compatible with a story of patent grants reducing asymmetric information problems

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<sup>14</sup>Interaction terms involving endogenous variables are themselves endogenous variables that need to be instrumented. We address this issue with the standard procedure of introducing, as additional instruments, the interaction between the experience measure and average examiner leniency.

in markets for inventors.

[Insert Tables 1 and 2 about here]

## 5.2 The scope of patent protection

The empirical exercise of the previous subsection relied on estimating the effect of getting an application approved thanks to a “lucky examiner draw”. This approach addresses the internal validity of the study, but may entail a problem of external validity. If the granting outcome is particularly sensitive to the leniency of the patent examiner for applications in the margin of the approval threshold, our results will capture a local average treatment effect for the group of inventors producing innovations around that frontier. In that case, it would be difficult to extrapolate our results to the whole population of applications and, in particular, to intrinsically more “patentable” applications, which tend to be more economically relevant.

To address this issue we propose to extend the concept of patent protection beyond the granted/non-granted dichotomy and focus on the number of approved claims as a more fine-grained measure of the same concept. Each claim in a patent document describes in technical terms a different element of the protected technology. As [Lanjouw and Schankerman \(2001\)](#) state, patent claims delimit the boundaries of the legal protection conferred by the patent. A larger set of claims implies that the patent covers a broader share of the technological space. As expected, patents with more claims run a higher risk of conflict with rivals and are therefore more likely to be involved in litigation ([Lanjouw and Schankerman, 2001, 2004](#)). Non-granted patents obviously have no approved claim, and an increasing positive number of claims implies an increasing scope of protection for the patent-holder. The applicant’s incentive is to claim as much as possible in the application though the examiner can narrow down these claims during the examination process ([Lanjouw and Schankerman, 2001](#)). The scope of patent protection is therefore affected by the examination process and influenced by examiner leniency. More lenient examiners do not only grant more patents, they also allow a larger number of claims per patent ([Cockburn et al., 2003; Lemley and Sampat, 2012](#)). Consequently, examiner leniency can also be used as an instrumental variable to estimate the effect of a greater scope of patent protection on inventor mobility. Furthermore, the whole population of

granted patents is subject to have more or less approved claims depending on the examiner’s leniency.

Table 3 presents the results of estimating the effect of the inventor’s approved claims on mobility. The number of claims can be readily obtained from patent documents and is also available from USPTO datasets. We first report the OLS estimate of the natural logarithm of the number of claims (plus one) and the usual set of controls on mobility. The OLS coefficient is negative and significant at the 1% level. In the next columns, we move to the IV specification where the number of claims is instrumented with our examiner leniency measure. Column 2 reports the first stage estimation, allowing us to explore the effect of examiner leniency on approved claims. The point estimate reveals that a one standard deviation increase in examiner leniency leads to a 0.15 standard deviation increase in claims, indicating that examiner leniency is also a strong instrument of the number of claims. Column 3 presents the second-stage regression, with a negative and significant coefficient estimate that indicates that a 10% exogenous increase in approved claims reduces the probability of moving by 0.19%. The 2SLS estimated effect is again substantially stronger than the one from the naive OLS model. As in the analysis of the effect of patent grants presented in the previous subsection, not accounting for the endogeneity of the stock of an inventor’s approved claims seems to induce an upward bias in the estimation of its effect on mobility. Finally, in order to check the extent to which these results are driven by the difference between non-granted patents (zero claims) and granted patents (positive claims), we repeat the analysis using information on granted patents only. As the coefficient from the last column of Table 3 shows, the estimated relationship between approved claims and mobility remains negative and strongly significant. The results from this last piece of analysis, however, have to be interpreted with caution since excluding inventors without granted patents from the analysis may induce some sample-selection bias.<sup>15</sup>

Overall, Table 3 suggests that the main finding presented in this paper -the negative effect of patent protection on inventor mobility- is robust to considering a

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<sup>15</sup>All results presented in this subsection stay robust to the use of the number of principal (or independent) claims (i.e. those defining the main novel blocks of the innovation) instead of the total number of claims (that also include dependent or subordinate claims). We collect the information on independent claims from the Patent Claims Research Dataset, available through the USPTO website.

more fine-grained measure of the scope of that protection, as measured by approved claims. Because heterogeneity in the scope of protection may exist at all levels of application patentability, the results presented in this subsection suggest that the appropriation effect of patent protection on mobility is not driven by a subset of inventors whose creations lie around the approval threshold, but it is rather a more general phenomenon.

[Insert Table 3 about here]

## 6 Heterogeneous impact of patent grants

The previous section documents a negative effect of patent protection on inventor mobility, which is consistent with the appropriability hypothesis. In this section, we explore several sources of heterogeneity in the relationship between patent grants and mobility, in order to evaluate the existence of further evidence supporting that hypothesis. We first examine variations in the effect across technology areas. By drawing on the distinction between discrete and complex technologies outlined by the existing literature, we assess whether the negative effect of patenting on mobility is stronger in discrete technologies, where patents arguably provide stronger protection. Secondly, we explore the role of different sources of knowledge firm-specificity affecting an inventor's stock of human capital. In particular, we look at cases in which the inventor's knowledge is especially valuable when implemented: (i) in collaboration with that of other inventors or (ii) in conjunction with some of her employer's key assets. We examine whether in those cases patents will play a less important role as a mechanism that turns inventor's knowledge into firm-specific capital and, thus, they will affect mobility less intensely. Finally, we examine whether patenting makes an inventor especially less likely to move to firms that are technologically similar to her current employer.

### 6.1 Variation across technology fields

In this subsection we examine whether differences in the effectiveness of patent protection across technology fields regulate the negative effect of patent grants on mobility. The traditional dichotomy between complex and discrete technologies can

be particularly useful in this respect. [Mansfield \(1986\)](#) and [Levin et al. \(1987\)](#) find that patenting is a key strategy for appropriating returns to R&D in pharmaceuticals and chemicals, while it is less important in most other industries. [Cohen et al. \(2000\)](#) push the question further and suggest that these differences are linked to the nature of technology and the physical character of the products. Their rationale is that the number of patentable elements in a new product importantly affects the way patents are used and, in turn, the degree to which they contribute to effective protection. In “discrete” industries, new products typically build on few clearly identifiable features. Hence, only one or a few number of patents are required to achieve an effective protection against imitation. This is the case in the pharmaceutical and chemical industries, where compounds are typically adequately protected by single patents. In contrast, new products in “complex” industries such as electronics require the input of numerous complementary components, typically protected by patents held by an array of third parties. This makes the protection conferred by a single patent on a new component inherently less valuable, since it is necessary to have or acquire the rights on other proprietary elements to be able to bring the new product into the market. Moreover, this ownership fragmentation makes it increasingly costly to assess infringement, facilitating inventing-around by rival firms (e.g., [Hall and Ziedonis, 2001](#); [Ziedonis, 2004](#)). For these reasons, patents are reported to be less effective against imitation in complex product industries relative to alternatives such as secrecy, lead time or complementary capabilities ([Cohen et al., 2000](#))<sup>16</sup>. The appropriability hypothesis suggests that patents reduce inventor mobility by impeding competitors’ ability to effectively use the knowledge generated by the inventor, thereby reducing her attractiveness to potential employers. Because effective protection implies that a firm can exclude others from using a patented invention in the marketplace, we should observe that the negative impact of patents on inventor mobility is more pronounced in discrete (as compared to complex) technology fields.

In order to empirically identify the technology field for each patent application, we rely on the NBER categorization. As there is no widely accepted classification

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<sup>16</sup>This claim is also line with the results of econometric studies that attempt to quantify the private value of patent protection across sectors (see, e.g., [Lanjouw, 1998](#); [Arora et al., 2008](#)).

scheme that links those categories to discrete or complex technology areas, we focus on clear-cut cases according to prior literature. Following [Levin et al. \(1987\)](#) and [Cohen et al. \(2000\)](#), we classify chemicals (category 1) and drugs (sub-category 31) as discrete, and computers and communications (category 2), medical instruments (sub-categories 32), biotechnology (sub-categories 33) and electric and electronics (category 4) as complex technology fields.<sup>17</sup> We then aggregate this information up to the inventor-application year level, and construct two time-variant dummy variables, *Discrete* and *Complex*, that equal one if the inventor’s largest share of applications up to spell  $t$  belongs to discrete or complex technology classes, respectively, and zero otherwise.<sup>18</sup> In our sample, the average mobility rate between two application years is 13% for inventors in discrete areas and 10% for those in complex areas.

We examine the impact of patents on mobility by technology fields using the instrumental variable discussed above. Column 1 of Table 4 provides estimates using the full sample. Specifically, we augment Equation (1) by including two instrumented interaction terms to capture how different appropriability regimes alter the effect of patents on inventor mobility. The coefficient on the first interaction term, *# of patents issued x Discrete*, is large and negative while that of *# of patents issued x Complex* is small and positive, although none of them are statistically significant. The corresponding Wald test indicates, however, that these two coefficients are statistically different from one another. These findings suggest, in line with the appropriability hypothesis, that the negative effect of patents on inventor mobility is stronger when inventors’ patent filings are concentrated in discrete technologies instead of complex fields. Columns 2 and 3 present the results of estimating our baseline 2SLS model separately for the subsamples of inventors working mainly in complex technologies and those working mainly in discrete fields. The results show that the effect of patent grants is large, negative and significant among inventors with their main expertise in discrete technology fields, whereas it is smaller among

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<sup>17</sup> Traditionally, biotechnology was classified as discrete, due to its intrinsic technological characteristics. However, the possibility to patent gene fragments since the late nineties contributed to the fragmentation of the patent rights needed for the commercialization of a product in this area ([Cohen et al., 2000](#)). This is why, following recent papers such as [Galasso and Schankerman \(2015\)](#), we classify it as complex. Results remain robust to the exclusion of biotech as a complex field.

<sup>18</sup> Because some technological areas are neither complex nor discrete, some 19,234 inventor-year observations are not assigned to either of the two categories

inventors in complex areas. One additional patent grant is expected to reduce the probability of moving by 2.2% for complex-regime inventors (a 22% decrease over the conditional sample probability of 10%) and by 5.4% for discrete-regime ones (a 41% decrease over the conditional sample probability of 13%). Finally, column 4 provides estimates using the combined sub-samples and interacting *# of patents issued* with *Discrete*. Consistent with the previous findings, the coefficient on the interaction term is negative and significant at the 10%.

[Insert Table 4 about here]

## 6.2 Other sources of firm-specific human capital

The second piece of additional evidence analyzes how different sources of an inventor's human capital firm-specificity shape the effect of patents on mobility. Workers' firm-specific skills are tied to a particular firm and have limited applicability to outside firms. This results in a lower relative outside value of employees' human capital in the labor market and leads to a lower probability of turnover (Becker, 1962). Specific human capital is typically used to explain empirical regularities such as the prevalence of long-term employment relationships and a negative relationship between tenure and the probability of separation (Parsons, 1972; Farber, 1999). According to our appropriability hypothesis, patents operate as a source of specificity of an inventor's human capital by creating a legally-induced gap between the inside and the outside value of her skills that reduces her probability of moving. We expect this effect to be weaker when complementarities with the current employer make an inventor's skills technically firm-specific. The reason is that, in this case, the inventor is unable to fully apply her skills with a new employer even if the underlying knowledge is not patent-protected. In contrast, when the inventor's skills are technically general and can be readily applied to alternative employers, patent protection should have a larger effect in reducing mobility.

In the context of innovation studies, the literature suggests potential sources of firm-specificity of inventors' human capital. First, Hayes et al. (2006) argue that firm-specificity derives from complementarities with the firm's other workers. In particular, by learning to work with each other over time, individual employees develop a stock of human capital that is specific to co-workers and difficult to re-build

with others. In the context of invention generation, [Jaravel et al. \(2015\)](#) show that inventors who experience an unexpected death of a co-inventor face a large and long-lasting loss of earnings and productivity. Thus, strong collaborative relationships such as those established in teams of inventors imply that each individual needs complementary units of knowledge from other inventors to extract the maximum value from her own knowledge. This makes departure decisions more costly for the inventor and reduces her relative attractiveness to outside employers, since competitors that aim to replicate a given set of knowledge must hire away the whole team ([Palomeras and Melero, 2010](#)). Second, [Lazear \(2009\)](#) suggests that most specific human capital is in fact a combination of general-purpose skills applied in a particular combination that is specific to the firm. Innovative companies tend to establish technological trajectories linked to their core competences, with accompanying patterns of standardized routines and procedures ([Nelson and Winter, 1982](#); [Hoetker and Agarwal, 2007](#)). This implies that the particular combination of skills employed by inventors in the company’s core areas is idiosyncratic to the firm and, therefore, difficult to transfer.<sup>19</sup>

We empirically explore the effect of the above-mentioned sources of firm-specific skills by using the following proxies: (i) the natural logarithm (plus one) of the number of unique co-inventors with whom an inventor has worked in her applications up to  $t$  and (ii) the percentage of her patent applications that fall in the firm’s core technology areas. Following [Song et al. \(2003\)](#), we consider a technology as core if its corresponding patent class appears with a frequency greater than 10% in the firm’s application portfolio (for the whole sample period). We control in these regressions for the inventor’s degree of specialization (captured by the number of different patent classes in which her applications fall) and firm size (proxied by the number of applications filed by the firm in that year), which are relevant controls to consistently estimate the effect of co-inventors and core.

Table 5 presents evidence on the interactions between both sources of firm-

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<sup>19</sup>Firm-specificity of core skills is illustrated by the following example. In 1970, Intel planned to invest in developing the first semiconductor DRAM (dynamic random access memory), the 1-kilobit 1103. However, despite its economic attractiveness, Intel’s engineers were seriously concerned about the potential negative consequences of developing knowledge and skills specific to DRAM technology. As noted by Gordon Moore, then CEO of Intel, “[t]here was a lot of resistance to semiconductor technology on the part of the core memory engineers. The engineers didn’t embrace the 1103 until they realized that it wouldn’t make their skills irrelevant” ([Cogan and Burgelman, 1989](#), p. 2-3).

specificity and patent grants on mobility. The first column reproduces our baseline model, to which we add the variables and controls mentioned in this subsection. We are interested in the interactions of the variables capturing firm-specificity of skills with the number of patents the inventor has been granted. In columns 2 and 3, we add these (instrumented) multiplicative terms separately. Column 4 shows the results for the full model. As expected, the figures from the interaction effects in columns (2) to (4) show that the negative impact of patent grants on mobility is most intense for solo inventors and for inventors working outside the firm’s core technologies. Both findings are consistent with the idea that patent protection operates as a retention mechanism that has its strongest effect in the absence of other sources of firm-specific human capital.

[Insert Table 5 about here]

### 6.3 Similarity between hiring firm and focal firm

In the last set of additional evidence, we explore how obtaining a patent affects different types of inter-firm moves. Inventors may be induced to leave their companies for a variety of reasons, and replicating their innovations elsewhere may be only one of them. Alternative employers with a technologically similar profile to that of the focal firm will be particularly interested in bidding for the inventor for knowledge-replication purposes, especially in the absence of patent protection. Technologically distant alternative firms, on the other hand, are relatively less likely to be motivated by replication intentions. Hence, according to the appropriability hypothesis, patent grants will have a particularly negative effect on the probability that inventors move to technologically similar employers.

To test this prediction, we characterize inter-firm technological similarity with a measure that captures whether the hiring and the focal firm overlap in terms of the core technology. Using the same definition of firm’s core technology area as in subsection 6.2, we create a categorical variable that is set to 0 when the inventor stays at the focal firm; to 1 when she leaves and at least one of the core technology domains of the new employer and the focal firm are identical; and to 2 when she leaves and there is no overlap in core areas. We then estimate a Multinomial Logit model that allows us to capture the effect of patent grants on the relative probability

of each type of move.<sup>20</sup> Table 6 shows the relative-risk ratios that result from the analysis. As the two first columns show, one additional patent issued reduces the relative risk that an inventor moves to both technologically overlapping and non-overlapping employers with respect to the omitted “stay” option (both relative risks are multiplied by a factor smaller than one after a patent grant). A comparison of the size of the estimated ratios suggests, as predicted, that the effect is more intense for the case of moves to employers with overlapping core technologies than for the rest of employers. The last column of Table 6 shows the relative-risk ratios corresponding to the election between the two types of moves, being mobility to employers with no core technological overlap the base category. As expected, the figures indicate that an additional patent grant significantly decreases the relative risk that a moving inventor switches to a technologically similar employer instead of switching to an unrelated one.<sup>21</sup>

[Insert Table 6 about here]

## 7 Discussion and conclusion

In this paper, we investigate the effect of patent protection on the mobility prospects of the authors of an invention. From a signaling perspective, patenting reveals information about the skills of the inventor to the market, thus attenuating asymmetric-information situations and making mobility more likely. From the appropriation perspective, patenting makes the inventor’s know-how relatively more valuable to her employer than to competitors, and should therefore reduce mobility.

In order to assess which of the two effects prevail, we examine the impact of getting a patent granted on the mobility patterns of the inventors involved in applications. Since inventions behind granted and not granted patents are expected to be inherently different, we adopt an instrumental variables approach to estimate the effect of patenting on inventors’ mobility. In particular, and following previous liter-

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<sup>20</sup>Again, we used the control function approach proposed by [Blundell and Powell \(2004\)](#) and [Wooldridge \(2014\)](#) to correct for the endogeneity of issued patents with the Average Examiner Leniency instrument in the Multinomial Logit model.

<sup>21</sup>In unreported extensions, we distinguish between whether the hiring firm’s core technology overlaps with the mobile inventor’s own specific technological expertise (instead of her previous employer’s core technology) to categorize moves. Replicating the specification of Table 6 for the alternative categorization produces similar results to those presented here.

ature, we use variations in the granting rates of patent examiners within an art unit (leniency). We analyze the early careers of inventors employed at firms who apply for patents in the USPTO for the first time between 2001 and 2012. Our results indicate that patenting causes a substantial decrease in the mobility of inventors in their early career. This result supports the appropriability hypothesis over the signaling hypothesis, suggesting that patent grants make the human capital more specific to the inventor’s current employer. Additional evidence provides further support to this hypothesis: (i) the negative effect of patents on mobility is particularly strong in “discrete” technologies where patent protection is more effective, (ii) patents have a less negative effect when complementarities with co-inventors or employer’s assets make an inventor’s knowledge set more difficult to transfer outside the company, and (iii) patents make inventors especially less likely to move to direct competitors. We address external validity concerns by extending the concept of patent protection to the number of approved claims. The results from the corresponding analysis suggest that the appropriation effect is present over the whole population of patent applicants and not only for those producing innovations in the margin of approval and rejection.

Whereas our results clearly indicate that any potential signaling effect of patent grants is offset by a strong appropriation effect driving down the mobility of inventors, they do not rule out the possibility that patent applications work as signals of inventor quality. Our analysis addresses the patent-granting effect of innovations that have been previously filed and (in most cases) made public. However, it is possible that signaling effects are mainly associated to the patent application and not to the grant, since it is at the time of the publication of the application when the information about the innovation and its inventors is released to the market. In this line, recent work by [Hoenen et al. \(2014\)](#) dealing with the signaling effect of patents in early-venture financing suggests a prevalent signaling role of patent applications over grants in the first round of venture-capital financing. Nevertheless, other research emphasizes the signaling effect of patent grants for new venture financing. [Häussler et al. \(2012\)](#), for example, suggest that the patent grant gives a “certification” with informative content for venture capitalists in addition to that conveyed by the application. We do not find analogous signaling effects of patent

grants affecting the mobility of inventors.

By supporting the appropriability hypothesis, the evidence presented in this paper indicates that patents, in combination with the prevailing property-right transfer contracts in technology sectors, make the human capital of inventors more firm-specific. This result has both public policy and managerial implications. First of all, it suggests that patents, despite making public some codified knowledge, may have the growth-reducing effect of hampering the diffusion of tacit know-how. Their negative effect on inventor mobility cuts down the spread of implicit knowledge associated with the protected technology and, more generally, may also reduce spillovers not related to the replicability of any specific innovation. Furthermore, this appropriation-induced reduction in mobility may also contribute to an inefficient allocation of inventor's skills. Evidence from [Hoisl \(2007\)](#) shows that inventors tend to experience productivity increases when they switch firms, suggesting that career moves are frequently motivated by employer-employee match improvements. To the extent that patents discourage mobility, they will also inhibit these improvements.

On the other hand, our results also suggest that patents generate a shift in incentives to invest in human capital from employee inventors to their employer patent-holders. This shift may encourage some efficient investments in training that might not have been otherwise carried out by the inventors themselves because of financial constraints or risk considerations.

In terms of managerial implications, our results suggest that inventors may not have strong incentives to generate patentable innovations if these decrease their outside options. Thus, firms that strongly rely on patent protection should complement that strategy with some internal incentive system that rewards patents (as documented by [Toivanen and Väänänen, 2012](#)).

Last but not least, our findings bring to light an important methodological issue. If patent grants affect the mobility prospects of the authors of the inventions, tracking inventors' careers through their issued patents (as most studies have done until now) introduces a downward bias in the detection of mobility. This bias may expand to analyses of causes and consequences of mobility as well. In order to avoid it, further studies at the inventor level should take into account both patent applications and grants.

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# Tables

Table 1: Summary statistics

Variable	Mean	SD	Min	Median	Max	Observations
Move	0.11	-	0	0	1	131485
# of patents issued	2.24	3.72	0	1	136	131,485
# of applications filed	7.66	11.10	1	4	305	131,485
Examiner leniency	0.004	0.09	-0.86	0.01	0.74	131,485
Years since 1st decision	3.04	2.03	1	2	11	131,485
# of claims issued	41.08	107.42	0	20	8,563	131,485
# of co-inventors	11.01	12.41	0	7	226	131,485
# of uspc classes	2.88	2.35	1	2	49	131,485
% of applications in firm's core	0.30	0.39	0	0	1	131,485
# of applications per firm	1262.92	1776.33	1	449	7,803	131485
<i>Application-level characteristics used in the Appendix</i>						
Family size	1.45	1.68	0	1	27	329,666
Applicant PAT references	4.30	13.36	0	0	105	164,832
Applicant NPL references	1.53	8.17	0	0	99	164,832
Applicant APP volume <sub>t-1</sub>	1261.36	1840.33	0	427	7,803	341,007

Table 2: Patent grants and inventor mobility

	Base and main results				Robustness checks	
	Base	Controlling for endogeneity			Adding non-linearity	Adding time dimension
		OLS (1 <sup>st</sup> st.) # of pats issued	2SLS (2 <sup>nd</sup> st.) Move	Probit (2 <sup>nd</sup> st.) Move		
Dependent variable	Move (1)	(2)	(3)	(4)	Move (5)	Move (6)
# of patents issued	0.001** (0.000)	-	-	-	-	-
Examiner leniency	-	1.705*** (0.060)	-	-	-	-
# of patents issued ( <i>instr.</i> )	-	-	-0.028*** (0.006)	-0.022*** (0.005)	-0.044** (0.019)	-0.048*** (0.015)
# of patents issued squared ( <i>instr.</i> )	-	-	-	-	0.002 (0.002)	-
# of patents issued × Years since 1st decision (L) ( <i>instr.</i> )	-	-	-	-	-	0.018 (0.011)
Years since 1st decision (L)	0.038*** (0.002)	1.310*** (0.014)	0.077*** (0.008)	0.069*** (0.006)	0.073*** (0.009)	0.043** (0.021)
First decision year FE	Included	Included	Included	Included	Included	Included
# of applications filed FE	Included	Included	Included	Included	Included	Included
Technological class FE	Included	Included	Included	Included	Included	Included
First-stage F-statistic	-	796	-	-	-	-

Notes:  $N = 131,485$ . Number of inventors: 69,136. Number of firms: 2,883. Estimation period is 2001 – 2011. Robust standard errors are clustered by inventor (in parentheses). Column (4) displays average marginal effects from a probit model with endogenous regressors. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 3: Claims and inventor mobility

Sample	All	All	All	Patents	Patents	Patents
Estimation method	OLS	OLS (1 <sup>st</sup> st.)	2SLS (2 <sup>nd</sup> st.)	OLS	OLS (1 <sup>st</sup> st.)	2SLS (2 <sup>nd</sup> st.)
Dependent variable	Move (1)	log(1+ claims) (2)	Move (3)	Move (4)	log(1+ claims) (5)	Move (6)
log(1+ claims) (L)	-0.002*** (0.001)	-	-	0.009*** (0.001)	-	-
Examiner leniency	-	2.499*** (0.048)	-	-	0.795*** (0.033)	-
log(1+ claims) (L) ( <i>instr.</i> )	-	-	-0.019*** (0.004)	-	-	-0.038** (0.015)
Years since 1st decision (L)	0.041*** (0.002)	0.599*** (0.006)	0.051*** (0.003)	0.036*** (0.002)	0.399*** (0.004)	0.055*** (0.006)
First decision year FE	Included	Included	Included	Included	Included	Included
# of applications filed FE	Included	Included	Included	Included	Included	Included
Technological class FE	Included	Included	Included	Included	Included	Included
First-stage F-statistic	-	2721	-	-	566	-

Notes:  $N = 131,485$  (111,921 in column 4 – 6). Number of inventors: 69,136 (57,926 in column 4 – 6). Number of firms: 2,883 (2,567 in column 4 – 6). Estimation period is 2001 – 2011. Robust standard errors are clustered by inventor (in parentheses). \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 4: Patent grants, technological areas and inventor mobility

Estimation method: 2SLS				
Sample	All	Discrete	Complex	Discrete and complex
Dependent variable: Move	(1)	(2)	(3)	(4)
# of patents issued ( <i>instr.</i> )	-0.027** (0.011)	-0.054*** (0.014)	-0.022** (0.009)	-0.020** (0.009)
# of patents issued × Discrete ( <i>instr.</i> )	-0.026 (0.018)	-	-	-0.034* (0.019)
# of patents issued × Complex ( <i>instr.</i> )	0.008 (0.014)	-	-	-
Discrete	0.070** (0.032)	-	-	0.063* (0.035)
Complex	0.008 (0.029)	-	-	-
Years since 1st decision (L)	0.072*** (0.009)	0.094*** (0.014)	0.072*** (0.013)	0.076*** (0.011)
First decision year FE	Included	Included	Included	Included
# of applications filed FE	Included	Included	Included	Included
Technological class FE	Excluded	Excluded	Excluded	Excluded
$N$	131,485	23,991	88,260	110,330
# of inventors	69,136	13,632	46,498	58,296
# of firms	2,883	1,277	1,823	2,523
Wald $\chi^2$	2.96*	-	-	-

Notes: Estimation period is 2001 – 2011. Robust standard errors are clustered by inventor (in parentheses). Wald tests for differences in coefficients between # of patents issued  $\times$  Discrete and # of patents issued  $\times$  Complex. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 5: Patent grants, firm-specific human capital and inventor mobility

Estimation method: 2SLS				
Dependent variable: Move	(1)	(2)	(3)	(4)
# of patents issued ( <i>instr.</i> )	-0.030*** (0.007)	-0.072*** (0.021)	-0.046*** (0.010)	-0.075*** (0.021)
# of patents issued × log (1 + # of co-inventors) (L) ( <i>instr.</i> )	-	0.021*** (0.007)	-	0.015* (0.008)
# of patents issued × % of applications in firm's core ( <i>instr.</i> )	-	-	0.041** (0.018)	0.035* (0.018)
log (1 + # of co-inventors) (L)	0.000 (0.002)	-0.043*** (0.016)	0.002 (0.002)	-0.031* (0.017)
% of applications in firm's core	-0.045*** (0.003)	-0.044*** (0.003)	-0.123*** (0.034)	-0.112*** (0.035)
# of uspc classes (L)	-0.022*** (0.004)	-0.017*** (0.003)	-0.009 (0.006)	-0.007 (0.006)
# of applications per firm (L)	-0.016*** (0.001)	-0.017*** (0.001)	-0.016*** (0.001)	-0.017*** (0.001)
Years since 1st decision (L)	0.076*** (0.009)	0.056*** (0.006)	0.081*** (0.009)	0.065*** (0.008)
First decision year FE	Included	Included	Included	Included
# of applications filed FE	Included	Included	Included	Included
Technological class FE	Included	Included	Included	Included

Notes:  $N = 131,485$ . Number of inventors: 69,136. Number of firms: 2,883. Estimation period is 2001 – 2011. Robust standard errors are clustered by inventor (in parentheses). \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 6: Patent grants and technological core of the hiring firm and the hired inventor's previous firm

Dependent variable	Core	Non-core	Core
	Move	Move	Versus
Estimation method: Multinomial Logit	Versus	Versus	Non-core
	Stay	Stay	Move
	(1)	(2)	(3)
# of patents issued ( <i>instr.</i> )	0.694*** (0.059)	0.849*** (0.052)	0.816** (0.080)
Years since 1st decision (L)	2.451*** (0.271)	2.036*** (0.163)	1.211 (0.161)
First decision year FE	Included	Included	Included
# of applications filed FE	Included	Included	Included
Technological class FE	Included	Included	Included

Notes:  $N = 131,485$ . Number of inventors: 69,136. Number of firms: 2,883. Estimation period is 2001 – 2011. Robust standard errors are clustered by inventor (in parentheses). Coefficients are expressed in terms of relative risk ratios. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

## Appendices

These Appendices provide additional material supporting the validity of the instrumental variable approach presented in the paper. In Appendix I, we present further evidence that the assignment of applications to examiners is plausibly random. In Appendix II, we discuss and report robustness checks for the first stage results.

### Appendix I: Investigating selection

The details of the examination process described in Section 4.2 of the article suggest that patent applications are assigned to examiners quasi-randomly within art units. Here, we provide further evidence that our proposed instrument (at the patent level) satisfies the exclusion restriction. For this restriction to hold, examiner leniency should only be related with inventor mobility through its influence on the probability that her patent application is granted. Therefore, we aim to test whether there is any correlation between the characteristics of patent applications (at the time of filing) that can be related with the likelihood that their authors move firms and our measure of examiner leniency (at the patent level). As discussed by [Lemley and Sampat \(2012\)](#), the assessment of whether a certain type of inventions are assigned to examiners with a certain leniency is challenging for two reasons: (i) it is difficult to identify variables that at the time of application would capture the characteristics of the underlying invention and (ii) much of the front-page information contained in patent documents is not available for applications.

One of the most important characteristics of patent applications that can affect the probability of their inventors to move is the value of the underlying innovation, since it is correlated with the inventors' ability ([Palomeras and Melero, 2010](#); [Ganco et al., 2015](#)). Though the most common measure to proxy for value of patented innovations (e.g. citations received) is not available at the time of application and, therefore, is not useful for our purposes, there is an alternative proxy for value that it is available at filing. This is the *patent family size*, i.e. the number of jurisdictions in which the application is filed. Because of the substantially higher costs of filing, one expects that applicants are more likely to seek broad international protection only if the invention is economically relevant ([Putnam, 1996](#)). Prior literature provides evidence that family size is correlated with a quality index of patents ([Lanjouw and Schankerman, 2004](#)), the likelihood that a patent will be granted ([Guellec and van Pottelsberghe de la Potterie, 2000](#)) and the economic value of patent rights ([Harhoff et al., 2003](#)). We define a patent family in terms of patent equivalents, using as our measure of family size the number of unique jurisdictions in which the focal U.S. patent application was filed at the time of application and protecting the same invention. We construct this measure using the algorithm described in [Martinez \(2010\)](#) on the data extracted from the Worldwide Patent Statistical Database (Patstat, April 2012 edition). We are able to recover this information for all of our patent applications filed between 2001 and 2011 provided

that, by January 2012, they were made public (patent applications are made public after 18 months from application or at the resolution date if this happens before). The final sample results in 329,666 observations for which we have non-missing values for examiner leniency and application data. We report the results of the OLS regression of *family size* on *examiner leniency* (as described in subsection 4.2.2) in Column 1 of Table A1. We use art-unit fixed-effects in order to control for potential patterns regarding family size across technologies. We find that the key coefficient on examiner is small (0.003) and insignificant (p-value = 0.877), suggesting that more lenient examiners are unlikely to be systematically assigned more valuable patent applications.

Another used measure for value of (potentially) patented innovations is the number of backward references. A relatively high number of references to previous patents and non-patent literature may indicate innovations of relatively high value, although this is not entirely unambiguous (see Harhoff et al., 2003). Given the importance of cited prior art in later litigation, the idea is that an applicant who seeks to protect a more valuable invention might have incentives to delineate the patent claims by inserting more references to prior art. Note that U.S. patent law imposes a duty of candor on patent applicants to disclose to the Patent Office any information that is “material” to the issuance of the patent (see 37 C.F.R. 1.56). A failure to do so may render the resulting patent unenforceable. We use then the number of applicant-submitted references to patent and non-patent literature at the time of filing available in Patstat. This data is only available though for the subset of applications that are eventually issued as patents. Also in this case, results suggest that there is no clear evidence that more lenient examiners get assigned applications that could protect potentially more valuable innovations.

Finally, we test whether there might be selection based on applicants’ size, since this may be a factor that could influence the likelihood of inventors to move. We use as a proxy for size the number of patent applications the applicant filed in the previous year. The last column of Table A1 report an insignificant coefficient on examiner leniency.

Table A1: Examiner relative leniency and application characteristics

Dependent variable	Family size	Applicant PAT References	Applicant NPL References	Applicant APP Volume <sub>t-1</sub>
Estimation method: OLS	(1)	(2)	(3)	(4)
Examiner leniency	0.003 (0.022)	0.433 (0.347)	0.223 (0.271)	-37.600 (26.413)
Filing year FE	Included	Included	Included	Included
Art unit FE	Included	Included	Included	Included
<i>N</i>	329,666	164,832	164,832	341,007
# of examiners	9,855	7,629	7,629	9,918

Notes: Estimation period is 2001 – 2011 in columns 1 to 3 and 2002 – 2011 in columns 4 and 5. Robust standard errors are clustered by examiner (in parentheses). \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

## Appendix II: Robustness tests for the first stage results

In this Appendix, we test whether our measure of examiner leniency (at the patent level) may be driven by technological effects within an art unit. Even though art units correspond to quite delimited technological areas, there may be sub-areas within an art unit that differ in the patentability of their applications. We can only distinguish these technological sub-areas by looking at the classes and subclasses to which the application is assigned to. Though art units are typically a more fine-grained classification of technologies (there are more art units than technological classes), in some cases there may co-exist different classes or, more frequently, different subclasses in an art unit (see <https://www.uspto.gov/web/patents/classification>). Therefore, we want to rule out that part of the variation in the measured leniency across examiners may be due to the variation in grant rates across technological (sub)classes within an art unit. This issue is particularly important because we do not conduct our analysis at the patent level but at the inventor level (i.e., we aggregate our relative leniency measure over the applications filed by a given inventor up to a given moment of time), and therefore we cannot include (sub)class fixed-effects in our empirical specifications. We explore whether the aforementioned technological effects may be a concern for our measure of examiner leniency by testing whether the correlation between examiner leniency and patent grant varies substantially when we include more fine-grained technological controls. Table A2 contains the results from this robustness test. Column 1 contains the baseline correlation between examiner leniency and patent grant without introducing any technological control. Note that our examiner leniency measure is constructed relative to the art unit and year (see Eq. (2) and (4) of the paper). This is why we obtain a very similar coefficient when we introduce fixed effects by art unit and year (column 2). Column 3 introduces art unit, year and class fixed effects, in order to control for the effects of classes that either expand over different art units or that share the art unit with another class. Next, we control for the most stringent fixed effects, at the art-unit, year and sub-class level (note that sub-classes are nested in classes). Across all these more stringent specifications, the correlation of examiner leniency and patent grant does not present substantial variations with respect to the baseline model, suggesting that our leniency measure is not the result of differences in the patentability across technological areas inside an art unit.

Table A2: Technology classification, examiner leniency and patent grants

Dependent variable: Patent grant				
Technology FE included	None	Art unit × Filing year	Art unit × USPC class × Filing year	Art unit × Sub-class × Filing year
Estimation method: OLS	(1)	(2)	(3)	(4)
Examiner leniency	0.737*** (0.008)	0.736*** (0.006)	0.720*** (0.006)	0.741*** (0.011)

*Notes:*  $N = 353,976$ . Number of examiners: 10,142. Number of art-units: 626. Number of USPC classes: 413. Number of sub-classes: 41,898. Estimation period is 2001 – 2011. Robust standard errors are clustered by examiner (in parentheses). \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .